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Resilience of road transport systems considering the stochastic response of travellers

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ABSTRACT: Human actors are seen as the main capability to enhance the resilience of road transport systems against disturbing scenarios. This paper compares different approaches to introduce users' behaviour into the resilience assessment. The consideration of the stochastic nature of human response combined with dynamic traffic modelling enables a comprehensive resilience assessment approach.

1. INTRODUCTION

Resilience of transport infrastructure has recently gained significant attention in the research community, e.g. Murray-Tuite (2006); Mattsson and Jenelius (2015); Nogal et al. (2016a), and among policy makers, e.g. Bostick et al. (2018); Nogal and O'Connor (2018).

To assess the resilience of networked infrastructure systems, various model-based approaches have been developed, e.g. Henry and Ramirez-Marquez (2012); Ouyang and Wang (2015).

Resilience assessment of road transport systems typically involves the application of traffic assignment models. These are often simplified models which aim to characterize the network's performance at various states of disruption and recovery. The actual performance of the system; however, includes several uncertainties. One such significant uncertainty is related to the role of the human actors, such as the operators and the users (Nogal et al., 2016b, 2018).

The current contribution illustrates the importance of consideration of stochastic user behaviour on the resilience assessment of transport networks, in particular, and the effect of using various levels of traffic modelling sophistication, in general. The different traffic assignment models and the resilience assessment procedure are described and the analysis of a case study is presented.

2. TRANSPORT INFRASTRUCTURE RESILIENCE

Transport infrastructure systems might be vulnerable to various types of hazards, such as extreme weather events, serious accidents, sabotage actions etc. These hazards could lead to a course of events which might significantly reduce the performance of parts of or the entire system. Since transportation is essential for the provision of vital functions for the society, i.e. multiple other important societal functions depend on transportation, it is important that the likelihood, the impact and the duration of disrupted system states should be limited.

In other words, the transportation network must be sufficiently resilient to foreseen, and, to some extent, even to unforeseen hazard scenarios. This means that the system should be properly prepared against, resist to, absorb and recover from any disturbing scenario, which implies enhancement in different domains of the system (e.g, technological and organizational domains).

Technological resilience assessments typically involve the prediction of possible future system states through analytic modeling or numerical simulation. Consideration of resilience in more general terms, i.e. including aspects other than technological, such as organizational, societal and economic ones is often done using holistic, indicator-based approaches, e.g. Pursiainen et al. (2016).

When a system is subjected to shock (sudden change) or crisis (sustained depression), its performance drops and time is required for both: 1) until a new equilibrium is found, and 2) restoration of full functionality. This is illustrated in the performance loss and recovery function, in Figure 1, for sustained disturbance, such as e.g. restrained traffic due to maintenance operations of a road network.

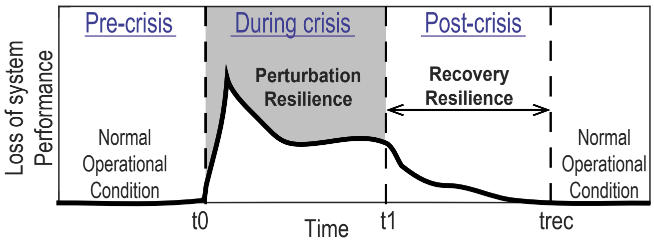

Figure 1: The performance loss and recovery function.

3. TRAFFIC ASSIGNMENT MODELS

When assessing the performance of transport infrastructure, modelling of the distribution of the traffic is required to obtain a picture about the traffic behaviour at various links (roads) and the system as a whole. Various mathematical models exist to assess the network's performance employing different levels of simplification of the real traffic flow.

Concerning the level of observation, the two major types of mathematical models for road traffic represent traffic flow either by 1) the explicit modelling of each individual vehicle (microscopic level), or 2) by the mass properties of the flow analogous to hydrodynamic models (macroscopic level). Microscopic models are typically based on numerical simulation, as each individual driver's behavior needs to be simulated. Thus, they can be very time-consuming for assessing the performance of larger networks. Macroscopic models, on the other hand, focus on network characteristics and provide analytic formulations to derive optimal conditions based on "average" user behaviour.

Road users are capable of acting individually, therefore, traffic has a certain stochastic nature. Nevertheless, the average user behaviour is governed by group dynamics as the user follows certain behavioural patterns due to formal and informal traffic rules and regulations which aim to reduce random behavior to increase road safety. Furthermore, with the help of traffic information management the uncertainties in the users' behaviour can be even more reduced and thereby the performance of the network improved. Thus, users represent an utterly important component of a transport system with regard to resilience as they both: pose potential risks and provide capability to the system at the same time (Nogal and O'Connor, 2017).

In the current paper the macroscopic modelling approach is used, since they are better suited for quantifying the network's performance as a whole, which is typically of main interest in resilience assessment.

3.1. *Macroscopic modelling*

Macroscopic assignment models describe how users select their routes for given or varying traffic conditions and thus how the traffic flow is distributed in the network. The traffic flow governs the network performance as it determines the travel time on various routes. Typically the problem is given as known (constant or changing) demands between various origins and destinations and the unknowns are the users traveling the different routes.

Mathematically, the system is defined by a set of nodes $\mathscr{N}$ and a set of links $\mathscr{A}$. To assess the systems performance a set of origin-destination (OD) node pairs, $pq \in \mathscr{D}$, are selected ($\mathscr{D}$ is a subset of $\mathscr{N}$ x $\mathscr{N}$). The OD pairs are connected by a set of routes R_{pq} with certain (positive) demands d_{pq} (in this paper corresponding to the daily peak values, as they represent the most critical situation). The actual traffic can be represented by a link flow $\mathbf{v} =$

$\{(v_a)_{a\in A}\}$, and a route flow $\mathbf{h} = \{(h_{pqr})_{r\in R_{pq}, pq\in\mathscr{D}}\}$ pattern. The flow at each link a is associated with a travel cost function c_a.

Static models consider traffic conditions stationary during the time of investigation and enable the calculation of the optimal traffic distribution assuming the the conditions are unchanged or represent average values. The optimal distribution is typically assumed as the so-called user equilibrium (UE). The user equilibrium is reached when "no vehicle can improve their travel time by unilaterally changing routes, and it is assumed that all the drivers have a perfect knowledge of the network and, hence, of the travel times" (Nogal, 2011).

$$\underset{\mathbf{h}}{\text{Minimize}} \sum_{a\in A} C_a(v_a) \tag{1}$$

subject to:

$$\sum_{r\in R_{pq}} h_{pqr} = d_{pq} \quad \forall pq \in \mathscr{D} \tag{2}$$

$$\sum_{pq\in D}\sum_{r\in R_{pq}} \delta_{apqr} h_{pqr} = v_a \quad \forall a \in \mathscr{A} \tag{3}$$

$$h_{pqr} \geq 0 \quad \forall r \in R_{pq}, \quad \forall pq \in \mathscr{D} \tag{4}$$

with

$$\delta_{apqr} = \begin{cases} 1, \text{if route } r \text{ from node } p \text{ to node } q \\ \text{contains arc } a; \\ 0, \text{otherwise,} \end{cases}$$

where $C_a(\cdot)$ is the integral of the travel cost function. Restrictions (2), (3) and (4) represent: the conservation of demand, the compatibility between link and route flows, and non-negativity of route flows, respectively. If both the objective function and the feasible region are convex, the above equations (1)-(4) provide a unique, optimal solution with respect to h_{pqr}.

3.2. *Dynamic traffic assignment*

The transient nature of resilience assessments motivates the use of dynamic traffic assignment models. Such a model is proposed by e.g. Nogal et al. (2016a). The model analyses the traffic response in discrete (daily) time steps. The response of each day depends on the conditions of the actual and the previous one. It is assumed that users do not select routes completely freely to achieve a minimum travel time (user equilibrium), rather they are restricted by their previous experience, which is characterized by the network's impedance α in the model. Therefore, the model is called dynamic restricted, equilibrium (DRE) model.

Mathematically, this is described by linking the route flows of two consecutive days:

$$h_{pqr}(t) = \rho_r(t) h_{pqr}(t-\Delta t) \quad \forall r \in R_{pq}, \quad \forall pq \in \mathscr{D} \tag{5}$$

where h_{pqr} is the flow (on route r with OD pairs pq), ρ_r denotes the variation of flow (on route r) in two consecutive time intervals and is restricted by the impedance, α, according to:

$$|\rho_r(t) - 1| \leq \alpha \quad \forall r \in R_{pq}. \tag{6}$$

This approach allows the impedance to be variable over time, $\alpha(t)$, and also variable for different ODs. The impedance of the system will hinder the traffic to instantaneously reach the equilibrium (minimum travel time) when an important perturbation occurs, requiring more time to adapt to the new situation.

The model permits the consideration of users' adaptation capacity, their incomplete knowledge about the new conditions and the other users' behaviour (Nogal et al., 2017). These aspects are relevant for assessing the system's resilience. The variation of flow ρ_r also provides information about the level of stress the road users are exposed to. If $\rho_r = 1$, the conditions on route r do not change compared to the previous time step, thus do not increase the stress level. However, if $\rho_r \neq 1$, users are either leaving or opting for route r, thereby contributing to increase stress.

3.3. *Stochastic modeling*

The main limitation of the deterministic traffic assignment is that it does not consider the stochastic user behaviour, i.e. that their route choices involve uncertainties and subjectivity: they make their choices somewhat arbitrary and based on how they personally perceive "travel costs". In fact, users might not always be rational and their preferences might differ (between individuals) and even vary (depending on the situation).

Traffic assignment models considering randomness in user's behaviour are referred to as stochastic user equilibrium (SUE) models. A relatively simple SUE model is provided by the C-logit approach (Cascetta et al., 1996), which provides an analytical formulation for the stochastic part of the problem.

The probability P_{pqr} of choosing a given route r between the OD pair pq is given by:

$$P_{pqr} = \frac{\exp\left(-\theta(c_{pqr}+F_{pqr})\right)}{\sum\limits_{l\in R_{pq}} \exp\left(-\theta(c_{pql}+F_{pql})\right)} \quad \forall r \in R_{pq}, \quad \forall pq \in \mathscr{D}, \quad (7)$$

where F_{pqr} and F_{pql} denote the commonality factors (for route r and l respectively); c_{pqr} and c_{pql} are the travel cost (for r and l) and θ is the dispersion parameter. The commonality factor takes into consideration that travellers are more likely to prefer routes which have several alternatives, and the dispersion parameter captures the level of dispersion of users in the traffic network as a consequence of users' subjectivity.

The C-logit SUE problem is presented in the form of mathematical optimization problem with regard to the total travel costs with penalizing low dispersion and high commonalities (which are based on the free-flow conditions), subjected to the restrictions in Eqs (2)–(4) (Zhou et al., 2012), given as:

$$\underset{\mathbf{h}}{\text{Minimize}} \sum_{a\in A} C_a(v_a) + \frac{1}{\theta} \sum_{pq\in\mathscr{D}} \sum_{r\in R_{pq}} h_{pqr} \ln(h_{pqr}) + \sum_{pq\in\mathscr{D}} \sum_{r\in R_{pq}} h_{pqr} F_{pqr}, \quad (8)$$

4. THE DSRE MODEL

For a dynamic extension of the static length-based C-logit SUE model, Eqs. (8) and (2)–(4) can be solved at each time interval, t. Following the approach in Nogal et al. (2016a), the continuity over time is provided by Restrictions (5) and (6), obtaining the following mathematical program, defined as dynamic stochastic restricted equilibrium (DSRE) model;

$$\underset{\mathbf{h}}{\text{Minimize}} \sum_{a\in A} C_a(v_a(t)) + \frac{1}{\theta} \sum_{pq\in\mathscr{D}} \sum_{r\in R_{pq}} h_{pqr}(t) \ln\left(h_{pqr}(t)\right) + \sum_{pq\in\mathscr{D}} \sum_{r\in R_{pq}} h_{pqr}(t) F_{pqr}, \quad (9)$$

subject to:

$$\sum_{r\in R_{pq}} h_{pqr}(t) = d_{pq}, \quad \forall pq \in \mathscr{D} \quad (10)$$

$$\sum_{pq\in D} \sum_{r\in R_{pq}} \delta_{apqr} h_{pqr}(t) = v_a(t), \quad \forall a \in \mathscr{A} \quad (11)$$

$$h_{pqr}(t) = \rho_r(t) h_{pqr}(t-\Delta t), \quad \forall r \in R_{pq}, \quad \forall pq \in \mathscr{D} \quad (12)$$

$$|\rho_r(t) - 1| \leq \alpha \quad \forall r \in R_{pq} \quad (13)$$

$$h_{pqr}(t) \geq 0, \quad \forall r \in R_{pq}, \forall pq \in \mathscr{D}. \quad (14)$$

The DSRE model is an extension of the DRE model, where the last two terms of the objective function, Eq. (9), introduce the C-logit stochastic users' behaviour. It is noted that the OD demand, d_{pq}, is constant over the analyzed time frame.

Accordingly, for each time interval, the DRE model presents a unique, optimal solution with respect to $h_{pqr}(t)$. This solution will correspond with the optimal solution obtained by the System (8) and (2)–(4) in case Eq. (13) is not active, that is, the impedance does not restrict the traffic system behaviour (e.g., when the perturbation is not highly disruptive). Otherwise, the optimal solution of the dynamic system (9)–(14) will be a sub-optimal solution of the static length-based C-logit SUE model, that is, the traffic network response is restricted by the system impedance.

The proposed formulation allows the resilience assessment of a traffic network, as explained through a case study in the following section.

5. CASE STUDY

5.1. *Description of the study*

To illustrate the effect of the choice of the traffic assignment model, the resilience assessment of the

Luxembourg-Metz highway and surrounding roads in France has been carried out. An overview of the network is given in Figure 2. It consists of 102 nodes connected by 278 links. 10 origin-destination pairs have been selected to analyze the network's performance. It is assumed that on a major section (see the dashed red lines in Figure 2) of the highway the traffic is restrained due to maintenance works from day between t_0=10 days and t_1=30 days. More details about the case study and the assumptions are given in Nogal and Honfi (2018).

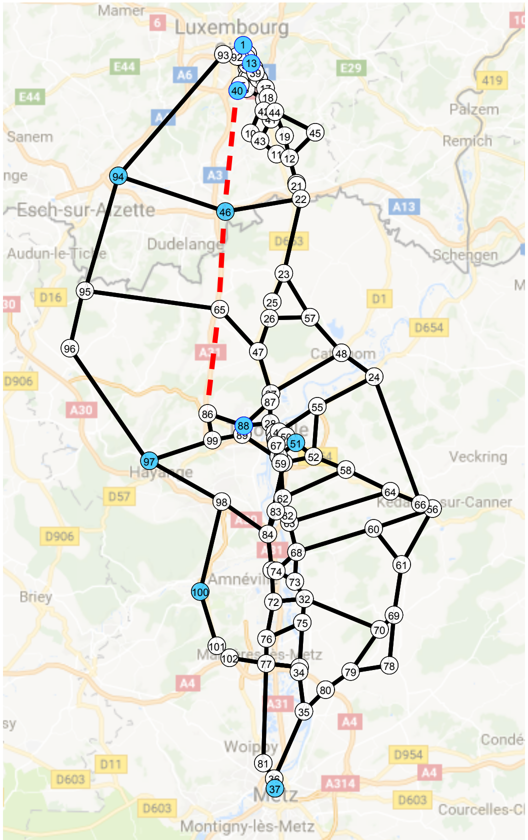

Figure 2: The studied Luxembourg-Metz road network on GoogleMaps. Blue nodes denote origins and destinations, dashed red lines denote service disruption.

The aim of the case study is to compare the effect of the choice of the traffic assignment model on the evaluated resilience of the system. Four models are compared, namely:

- Static, deterministic, user equilibrium (SDUE). The model in Subsection 3.1, applied at each time interval without a temporal connection, that is, deterministic traffic behaviour responding only to the current conditions.
- Static, stochastic, user equilibrium (SSUE). The model in Subsection 3.3, applied at each time interval without a temporal connection, that is, stochastic traffic behaviour responding only to the current conditions.
- Dynamic, deterministic, restricted equilibrium (DDRE). The model in Subsection 3.2, that is, deterministic traffic behaviour with users responding to both the previous and the current conditions.
- Dynamic, stochastic, restricted equilibrium (DSRE). The model in Section 4, that is, stochastic traffic behaviour with users responding to both the previous and the current conditions.

In each model the travel cost c_a for a given link a is calculated according to the BPR function, $c_a = c_a^0 \left[1 + m\left(\frac{v_a}{v_a^{max}}\right)^b\right]$, where c_a^0 is the free-flow travel time, v_a^{max} is the capacity of the link (1800 vh/h/lane), m and b are empirical parameters, based on the observed travel times and flows at selected links.

5.2. *Performance measures*

The quantification of the network's resilience is based on the the calculation of three performance measures, such as stress, cost and the exhaustion as defined by Nogal et al. (2016a), see further details in the referred paper.

The stress level for a given perturbation κ of the original equilibrium of the system is given by:

$$\sigma_\kappa(t) = \max_{pq \in D} \left(\frac{1}{\alpha} \frac{\sum_{r \in R_{pq}} |\rho_r(t) - 1|}{n_{pq}} \right), \tag{15}$$

where n_{pq} is the number of routes with OD pair pq. $\sigma_\kappa(t)$ is defined in the interval $[0,1]$, that is, between the equilibrium state and the total exhaustion of the adaptation capacity, respectively (Nogal et al., 2016a).

The cost level for a given perturbation κ is calculated as:

$$\tau_\kappa(t) = \frac{C_T(t) - C_0}{C_{th} - C_0}, \tag{16}$$

where $C_T(t)$ is the actual total cost (the sum of the travel costs of all links at each time interval), C_0 is the initial total cost (at $t = 0$), and C_{th} is a cost threshold associated with the largest acceptable cost experienced by a traffic network under a perturbation. In this example, a value of twice the initial total cost at peak hour has been assumed.

The level of exhaustion for a given perturbation κ is defined as the weighted sum of stress and cost, $\psi_\kappa(t) = (1-w)\sigma_\kappa(t) + w\tau_\kappa(t)$, with $w \in [0,1]$. In this example, $w = 0.75$.

5.3. *Quantification of resilience*

The system resilience associated with the immediate response to the perturbation κ, is calculated here as the normalized area over the performance loss and recovery function (or exhaustion curve):

$$\chi_\kappa^p = \frac{\int_{t_0}^{t_1} (1 - \psi_\kappa(t))\, dt}{t_1 - t_0} \tag{17}$$

where t_0 and t_1 denote the initial and the final times of the disruption.

The resilience of the network associated with recovery after the perturbation κ has finished, is calculated as:

$$\chi_\kappa^r = \max\left\{\left(1 - \frac{t_{rec}}{T_{th}}\right); 0\right\} \tag{18}$$

where t_{rec} denotes the time required until a new equilibrium is achieved after the disruption, and T_{th} is a threshold concerning the largest acceptable time for recovery. In this example, 30 days has been considered as the maximum acceptable time to recover.

The total resilience is calculated as the average of the two aforementioned resilience characteristics (i.e. perturbation and recovery resilience), $\chi_\kappa = \frac{1}{2}\left(\chi_\kappa^p + \chi_\kappa^r\right)$. It should be noted that these two aspects could be combined with uneven weights based on the evaluator's (typically the network operator) preferences.

5.4. *Results*

First the two static models, SDUE and SSUE, are applied to the case study. Practically it means a traffic assignment exercise to find the user equilibrium for both, the original (and thus also the fully restored) and the disrupted state of the network.

The evolution of the selected performance measures (stress, cost and exhaustion level) are presented in Figure 3: dashed green line - SDUE and continuous blue line - SSDE (note that a black line indicates the duration of disruption in the top of the figure). The results are quite similar for both cases. The stress level (top of the figure) is not captured by the static models. The cost (middle) and the exhaustion level (bottom) increase during the maintenance operations and recovers immediately after they are finished. The evaluated total resilience for both cases are very similar. Thus, the consideration of stochastic behaviour has little effect on the evaluated resilience of the system.

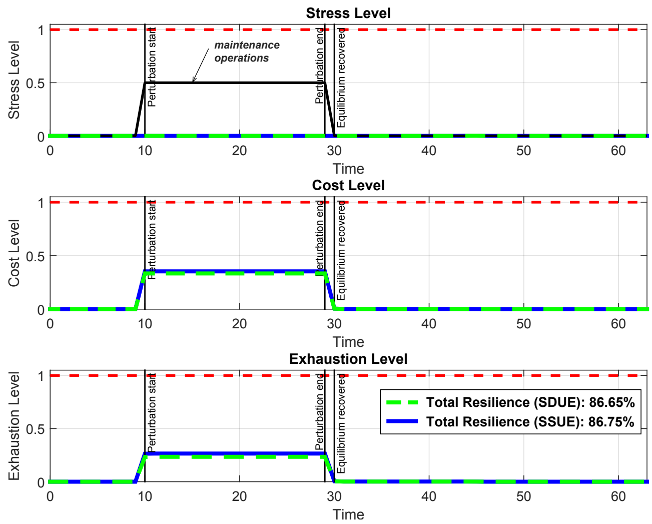

Figure 3: Evolution of performance using the static models (SDUE and SSUE).

The next step involves the application of the dynamic traffic assignment models in the resilience assessment. The results are presented in Figure 4: DDRE - dashed gray line and DSRE - continuous blue line.

The characteristic of the curves significantly differ from each other and from the ones obtained by the static models. In both cases, i.e. DDRE and DSRE, the stress level (Figure 4: top) increases when the system changes states (i.e. at the beginning and the end of the maintenance works). However, with the deterministic model (DDRE) the

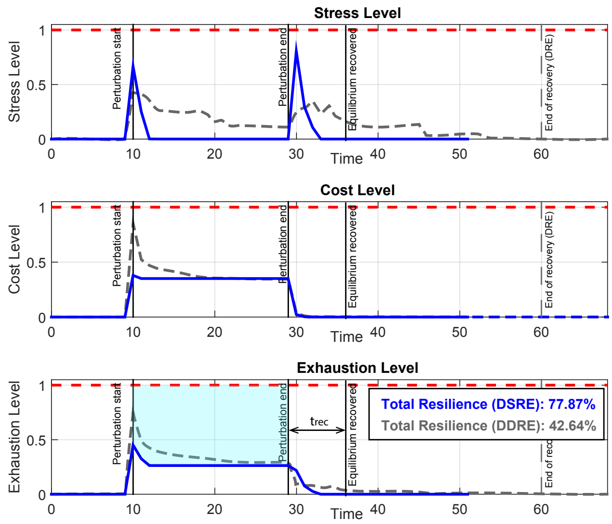

Figure 4: Evolution of performance using the dynamic models (DDRE and DSRE).

relaxation is elongated, whereas with the stochastic model (DSRE) rather short and sharp "stress-peaks" can be observed. The cost level curve (Figure 4: middle) is also quite different. With the deterministic model (DDRE), a peak is present at the beginning of the perturbation, but not at the end of it. On the other hand the stochastic model (DSRE) results in a similar cost evolution to the one obtained by the use of the static models. The exhaustion (Figure 4: bottom) is a mixture of the other two performance measures: it has a slight peak at the start of the perturbation and also shows a certain "viscous relaxation" following state changes.

Concerning the total resilience, the final value obtained by the DDRE and DDSRE differs significantly. The results of the resilience assessment using the four different traffic assignment models are summarized in Table 1.

Table 1: Comparison of results.

Model	C_0 [']	τ_k [%]	t_{rec} [d]	χ_κ^p [%]	χ_κ^r [%]	χ_κ [%]
SDUE	18.3	24.8	0	73.3	100.0	86.7
SSUE	18.7	25.3	0	73.5	100.0	86.8
DDRE	18.3	var.	60	85.3	0	42.6
DSRE	18.7	var	36	79.1	76.7	77.9

The initial total cost C_0 are similar for all models. The cost level during the perturbation $\tau_\kappa(t)$ is constant (but slightly different) for the two static models and variable in the dynamic models. The recovery time is t_{rec} is immediate (0) when static models are applied; however, they are quite different with the dynamic assignment models (60 and 36 days for DDRE and DSRE, respectively).

As a result of these the recovery resilience χ_κ^r is at maximum (100%) when evaluated with the static models. On the other hand, when the dynamic, deterministic model (DDRE) is used, the recovery resilience χ_κ^r will be zero. As a consequence of this the total resilience χ_κ total resilience values will be quite different for these cases and might seem unreasonable. The application of the DSRE model, however, gives more realistic results concerning resilience.

6. CONCLUSIONS

Four traffic assignment models have been compared with different levels of human response consideration; the SDUE model that assumes users have perfect knowledge of traffic conditions and an unlimited capacity of adaptation to changes; the SSUE model that includes the subjective perception of traffic conditions; however, an immediate capacity of recovery; the DDUE, which restrict users' capacity of adaptation due to lack of knowledge of the new situation and of the behaviour of other users, however users make objective decisions based on this knowledge; and finally, the DSRE, which assumes users have incomplete knowledge of the traffic conditions and make subjective decisions.

The models assuming immediate restoration of equilibrium (SDUE and SSUE) can be used to capture steady situations, such as a disturbing scenario held over time. However, they do not provide information on the stress level of users under changing scenarios and on the recovery process.

On the other hand, models considering that mobility patterns are the consequence of rational decisions based on perfect perception of information (DDRE model) are only valid to have an idea of the averaged behaviour of the traffic system. Nevertheless, the averaged values cannot be used when assessing the resilience of a traffic network, given that the stochastic response of users provides the system with different mechanisms to cope with the disturbing scenarios.

In the presented case study, the randomness of users' behaviour due to differing perceptions and/or irrational decisions (DSRE model) resulted in more concentrated stress after changing the traffic conditions; however, they are able to adapt to the new conditions and to recover quicker. It should be noted, that using the DSRE model does not necessary gives higher resilience (Nogal and Honfi, 2018), rather more realistic mobility patterns.

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